CESM Tutorial Workshop
July 11, 2025

Earth System Prediction using CESM

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CGD, NCAR

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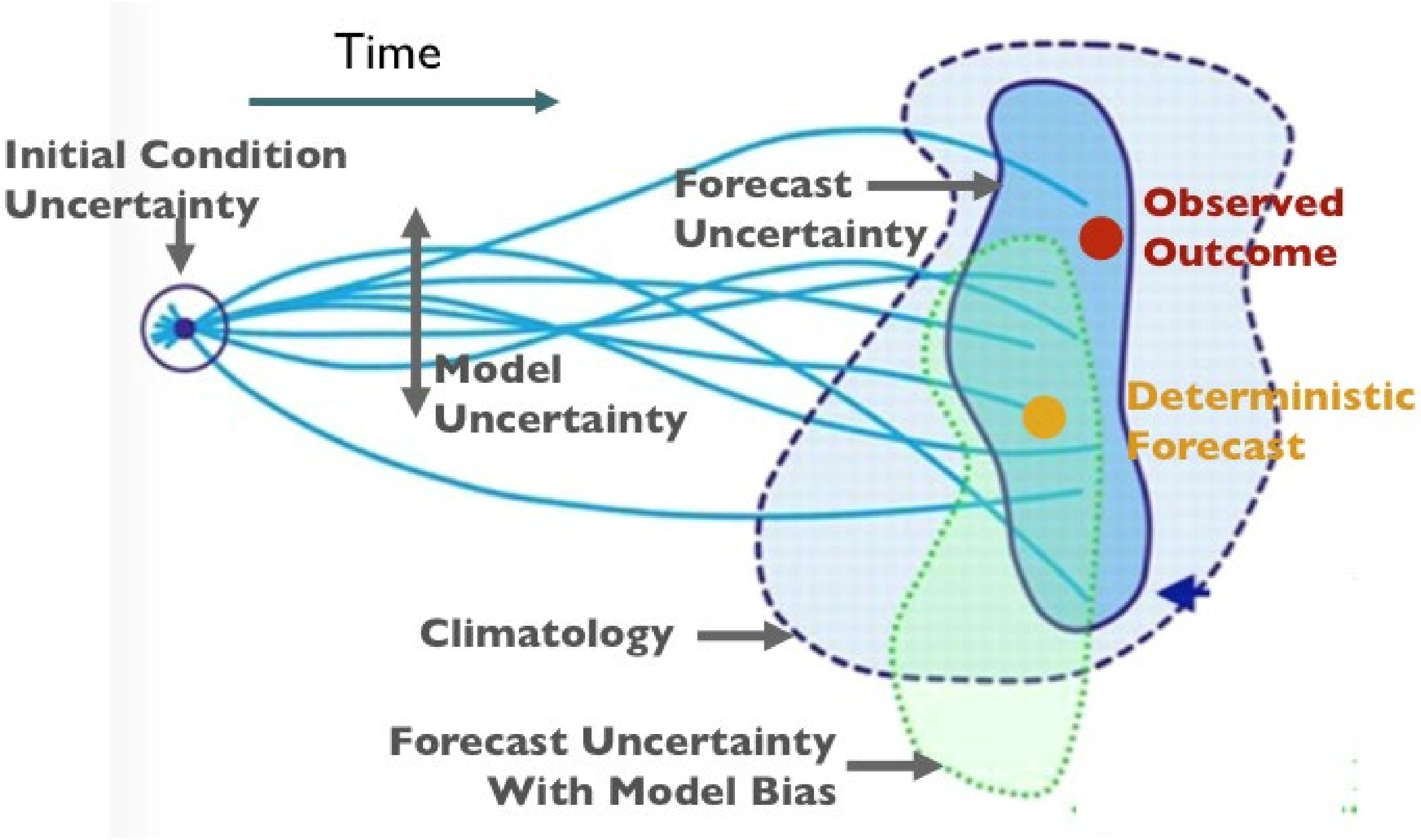
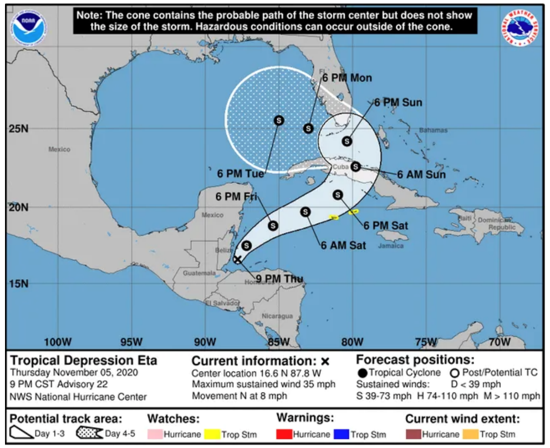
Probabilistic Weather Forecasting

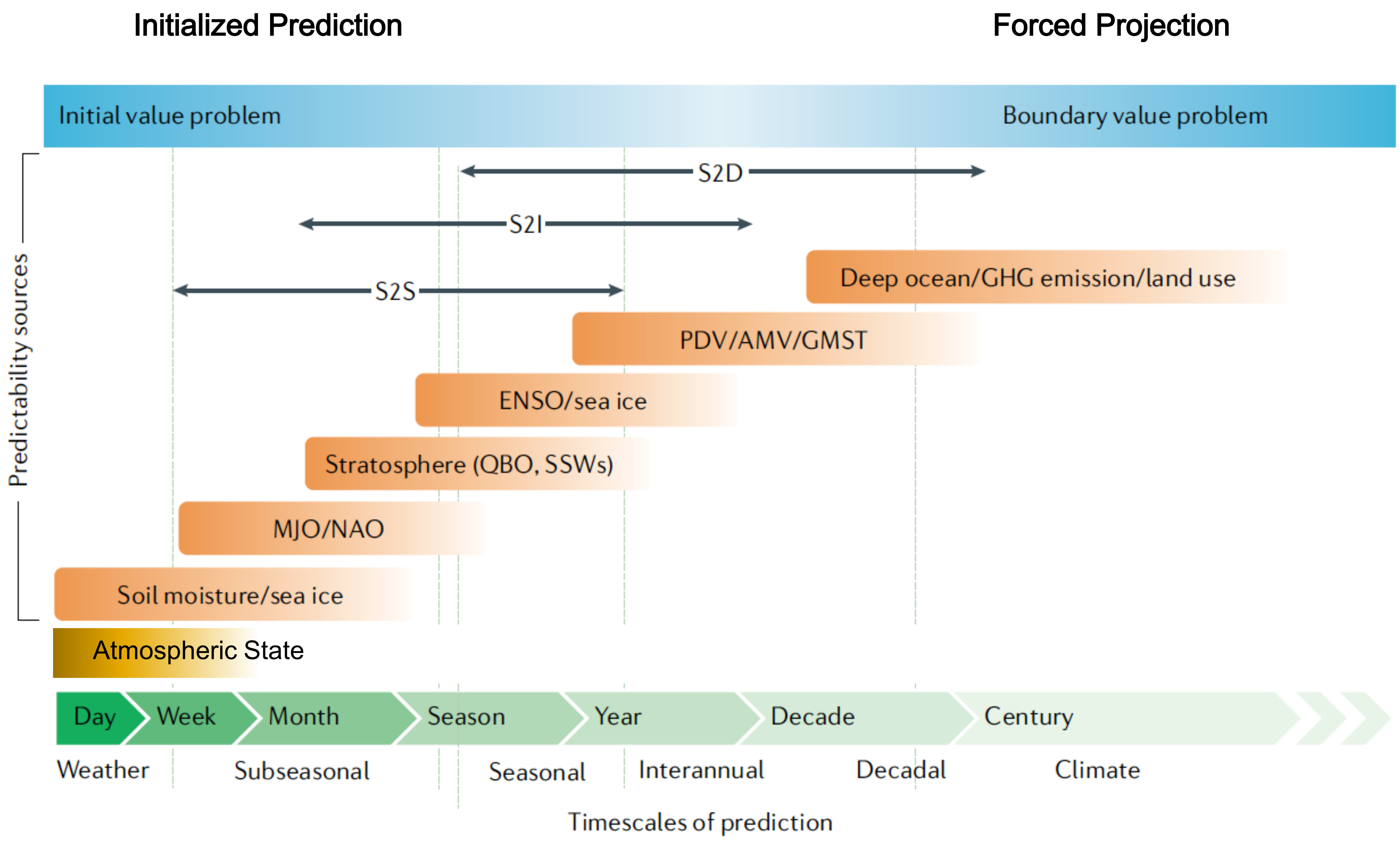
- Initialized ensembles generate probability distributions of future states
- Ensemble mean ➔ most likely outcome (deterministic forecast, “**signal**” that is common across ensemble members)





Slingo & Palmer (2011, doi:10.1098/rsta.2011.0161)

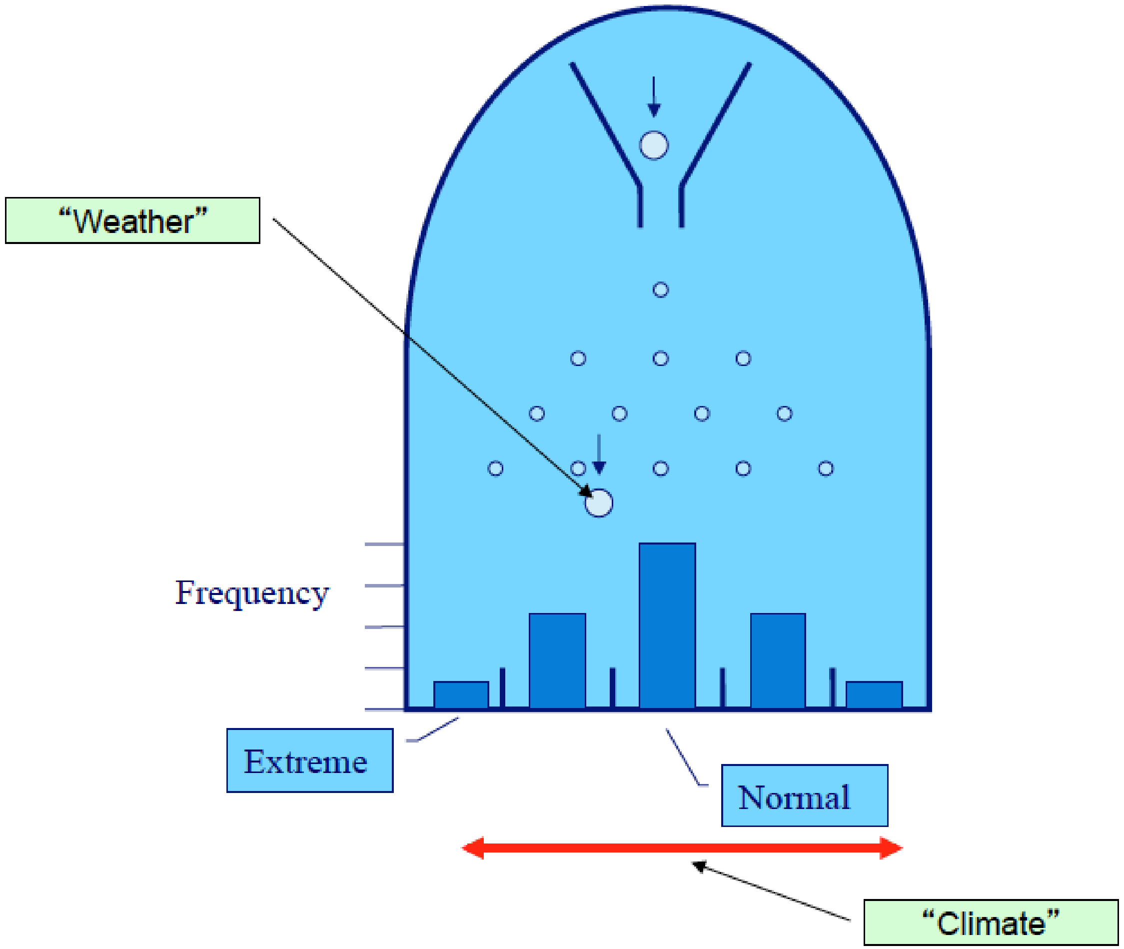
Sources of Climate Predictability



Merryfield et al. (2020, 10.1175/BAMS-D-19-0037.1)
Meehl et al. (2021, 10.1038/s43017-021-00155- x)

Weather vs. Climate

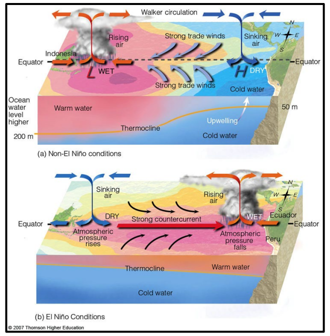
- Climate is the background probability distribution of weather



Weather vs. Climate

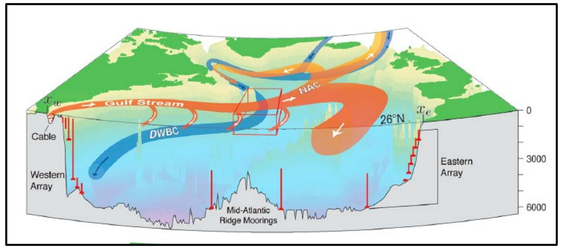
Emissions

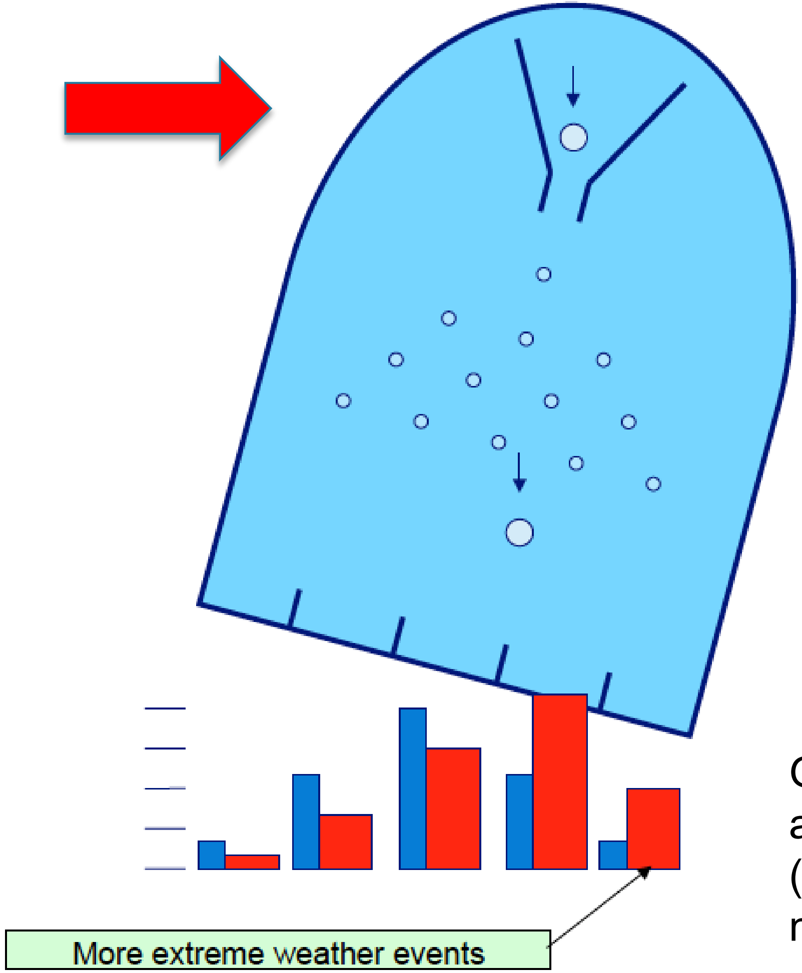
ENSO Cycles



Volcanic Eruptions

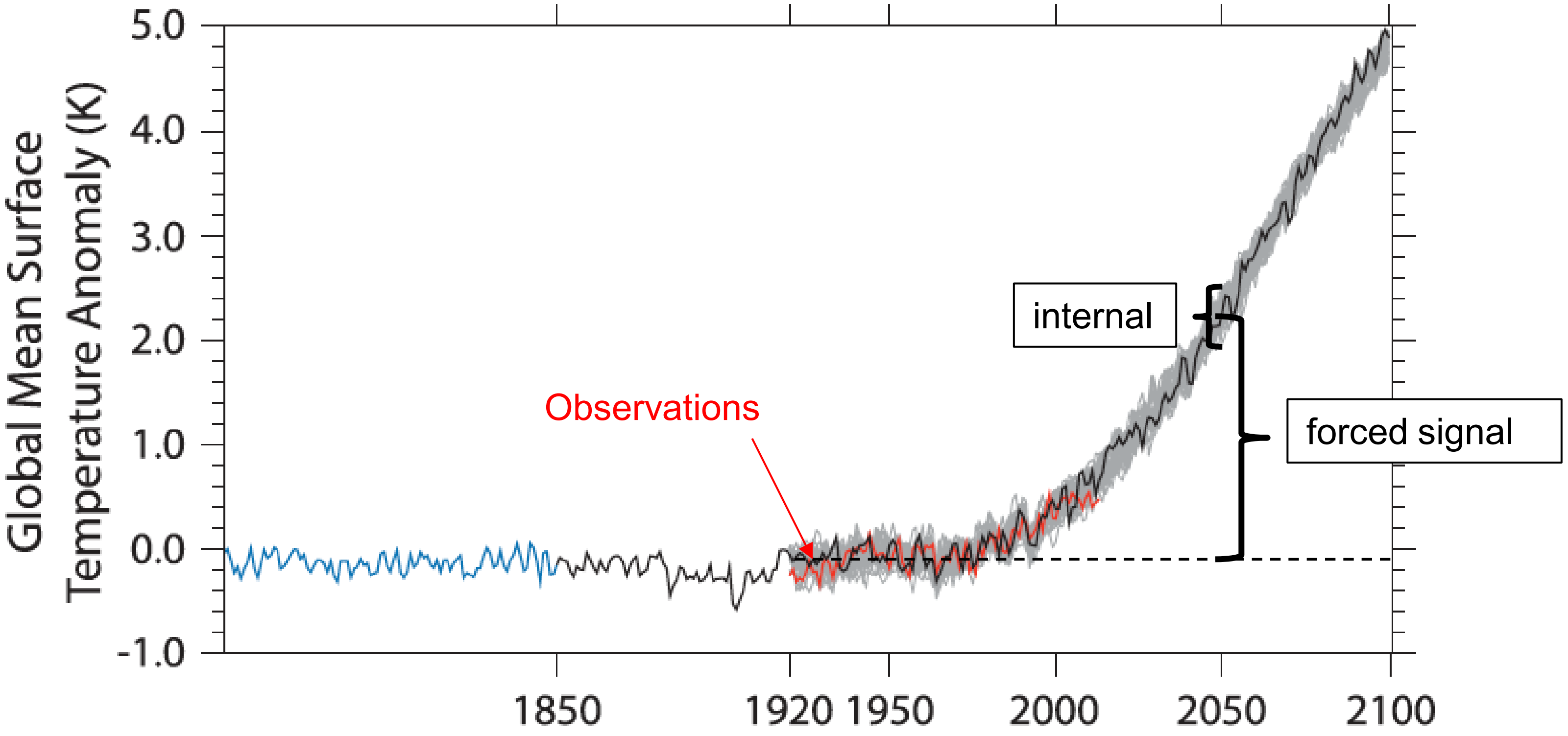
Ocean Heat Transport





Goal of climate prediction is to anticipate changes in climate (i.e. future weather statistics, not future weather events).

Climate Projection Large Ensembles



https://esgf-data.dkrz.de/projects/mpi-ge/

Ensemble spread develops from slight differences in initial conditions

Predicted “signals” depend solely on forcing applied

Permits decomposition into forced vs. internal variability

Kay et al. (2015, 10.1175/BAMS-D-13-00255.1)

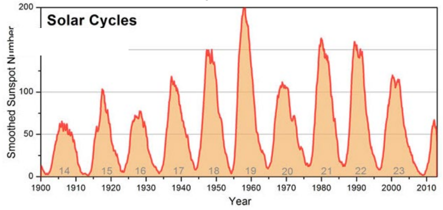
Forced Variability & Change

Greenhouse Gases

Biomass Emissions

Volcanic Eruptions

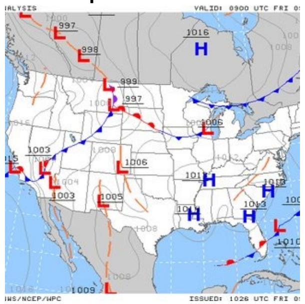
Solar Cycles



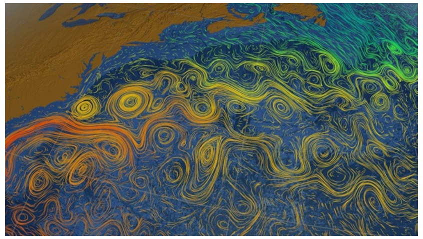
Regional Environmental Change

Internal Variability

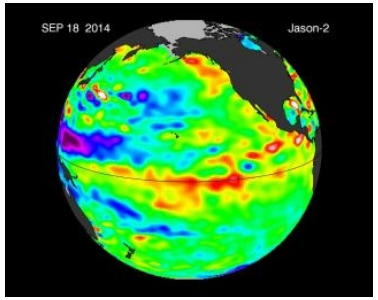
Atmospheric Turbulence



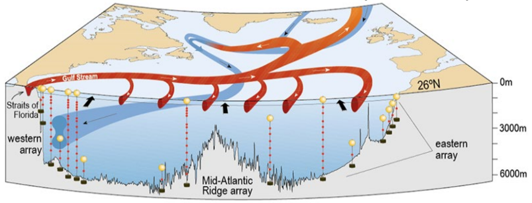
Oceanic Turbulence



El Niño/La Niña



Atlantic Meridional Overturning Circulation (AMOC)



Forced Variability & Change

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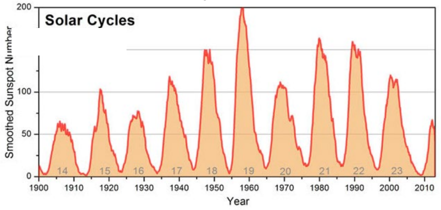

Regional Environmental Change

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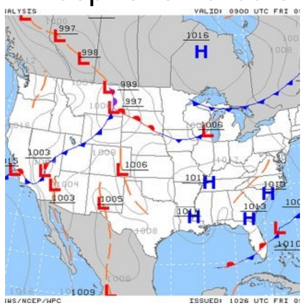

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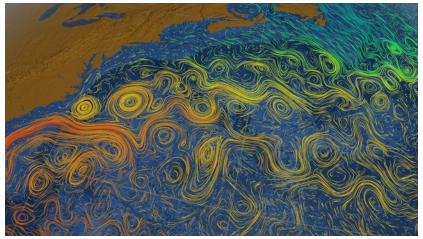

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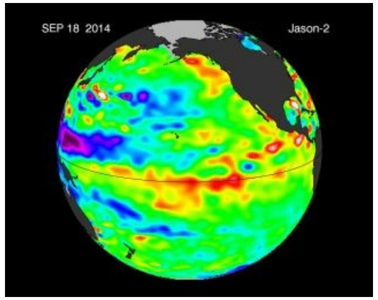

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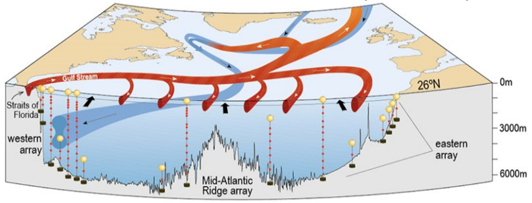


Projection Large Ensembles (“uninitialized”)

Ensemble mean (signal) = forced variability/change

Ensemble spread (noise) = internal variability (“irreducible uncertainty”)

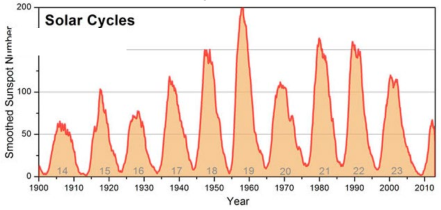
Forced Variability & Change

Greenhouse Gases

Biomass Emissions

Volcanic Eruptions

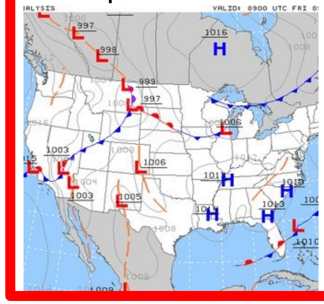
Solar Cycles



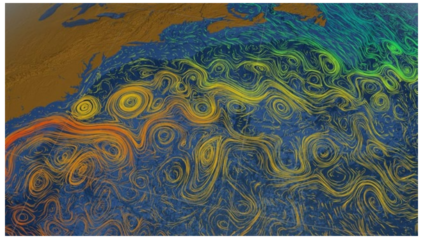
Regional Environmental Change

Internal Variability

Atmospheric Turbulence



Oceanic Turbulence



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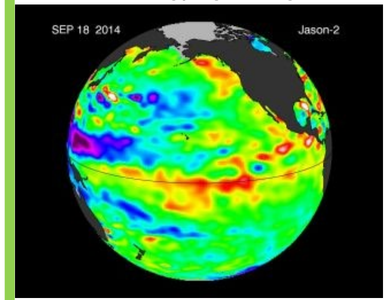

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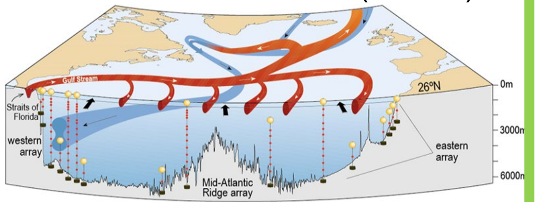
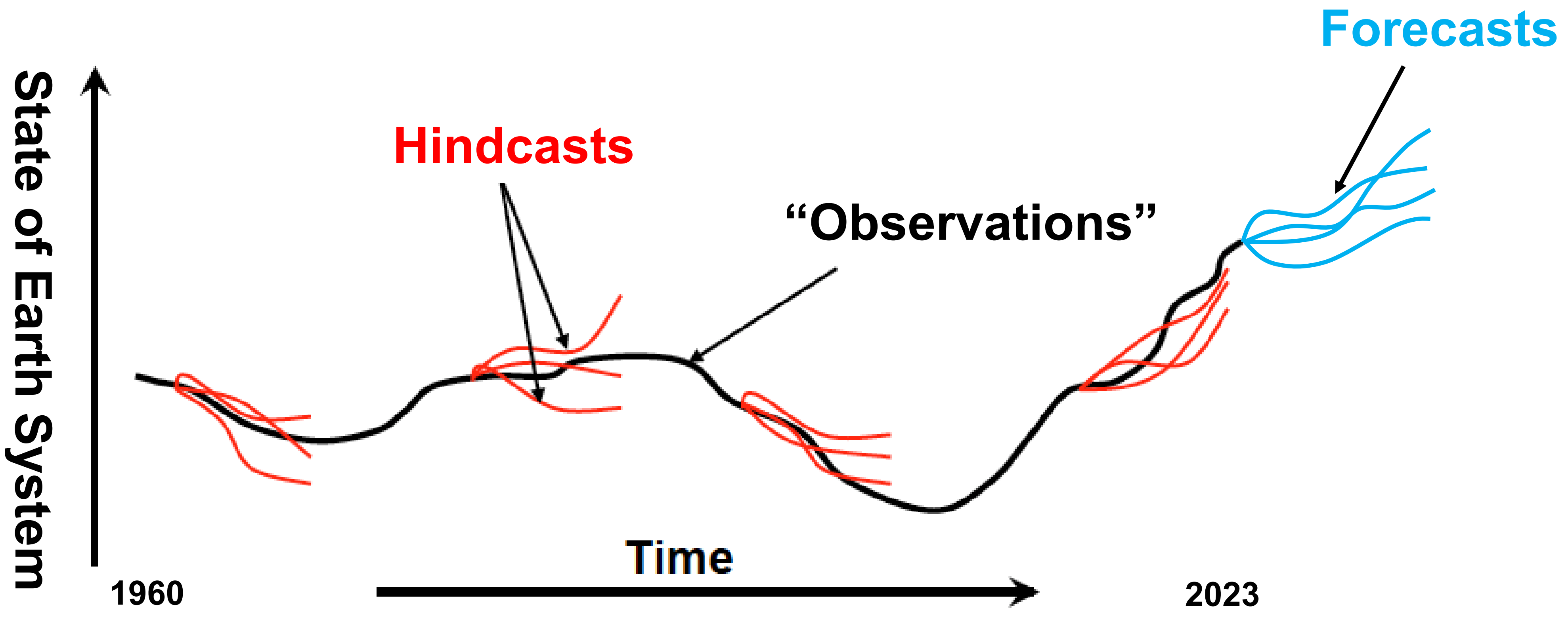


Initialized Prediction Ensembles

Ensemble mean (signal) =
forced variability/change +
predictable internal variability

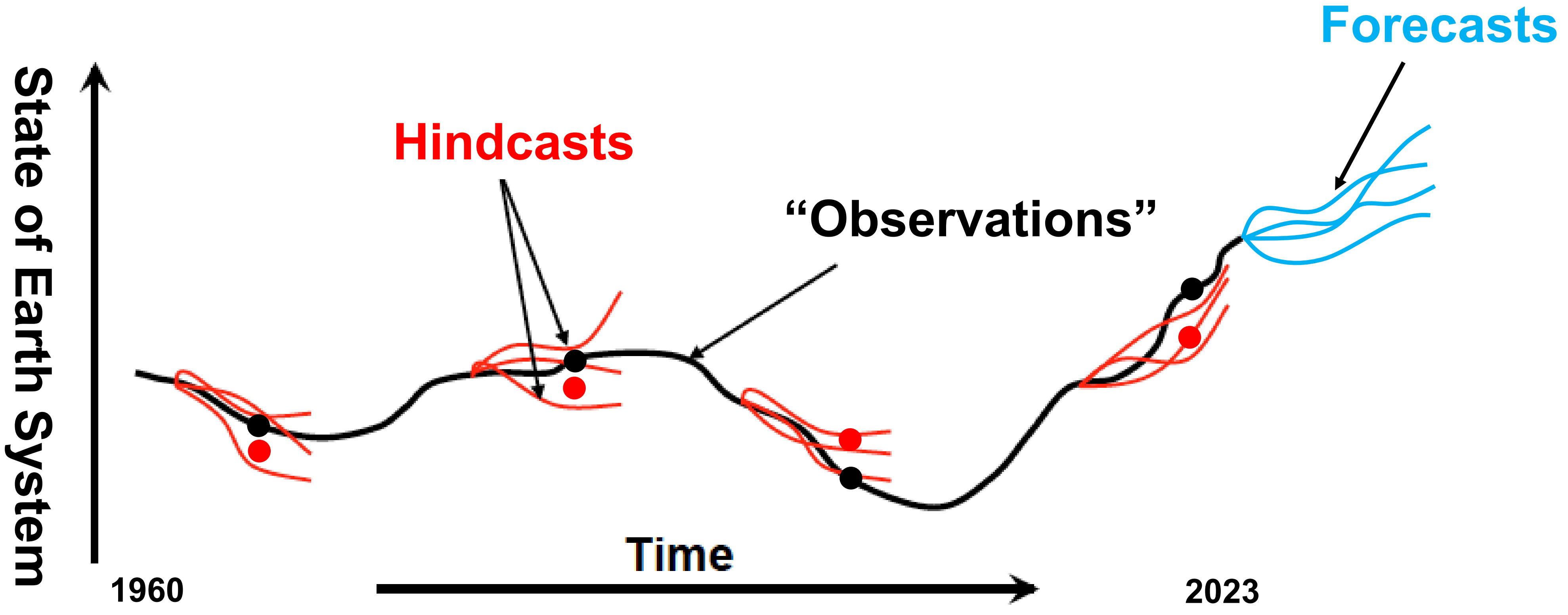
Ensemble spread (noise) =
unpredictable internal variability

How does initialized climate prediction work?



1. Initialize climate model simulations from best estimates of the historical Earth system state
2. Force the simulations with observed external forcings
3. Repeat steps #1-2 many times, to generate a collection of "hindcasts".
4. Use hindcasts to evaluate model skill at predicting past change.
5. If model has hindcast skill, then forecasts (using projected forcings) of future change are more credible.

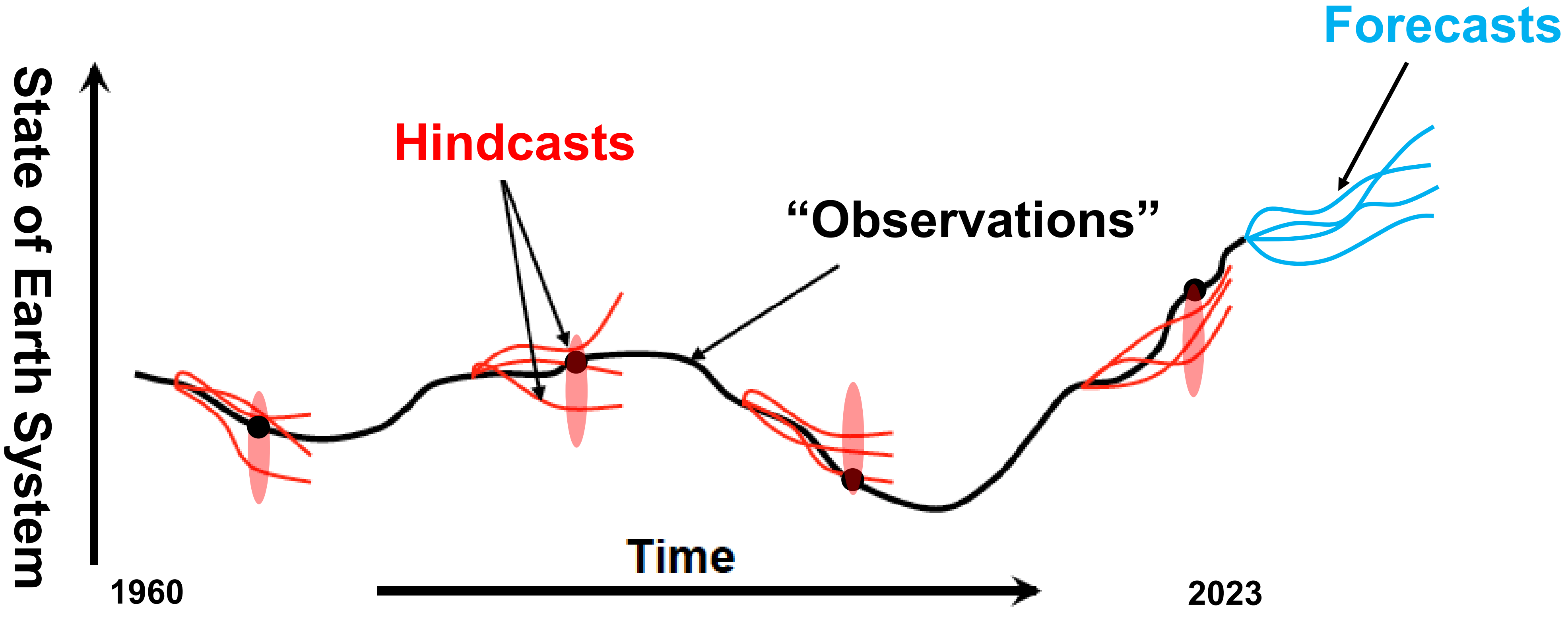
How does initialized climate prediction work?



Deterministic Skill

e.g., Anomaly Correlation Coefficient (ACC)

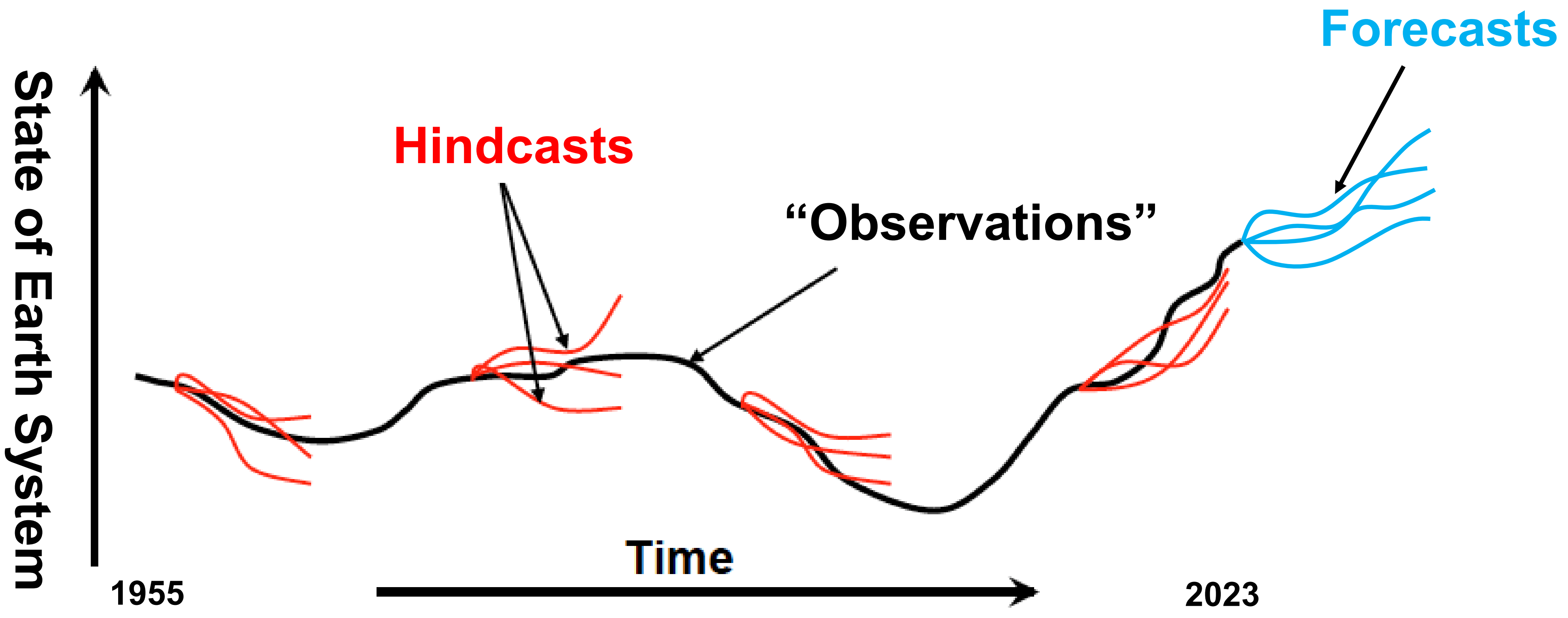
How does initialized climate prediction work?



Probabilistic Skill

e.g., Brier Skill Score (BSS)

How does initialized climate prediction work?



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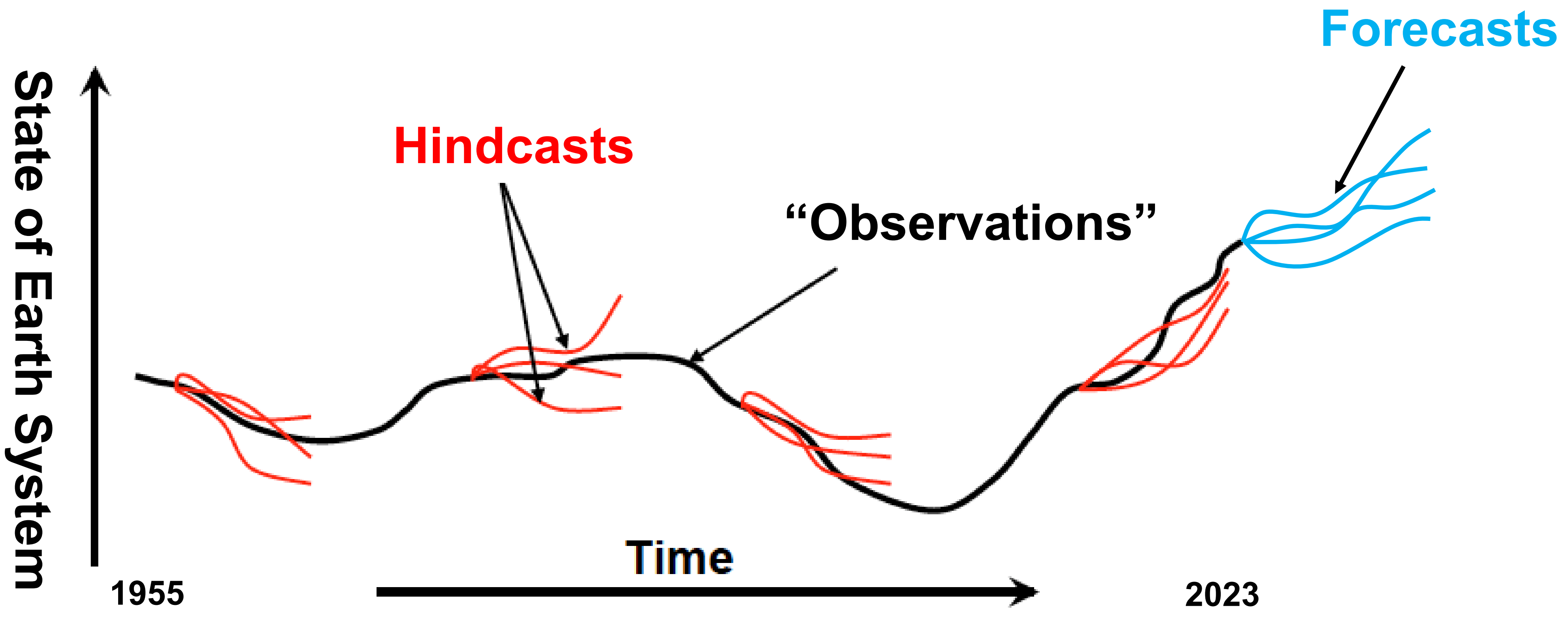
🡐 This helps in predicting **internal** variability signals

How does initialized climate prediction work?



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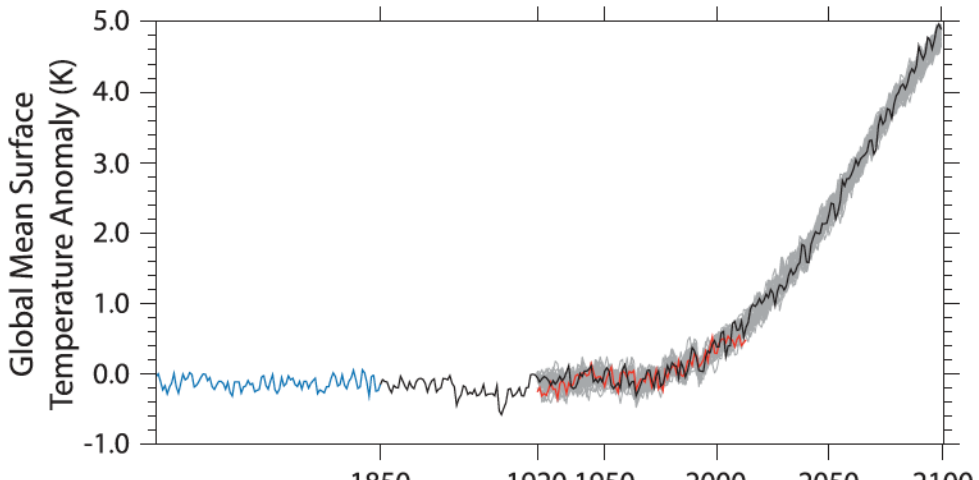
5. If model has hindcast skill, then forecasts (using projected forcings) of future change are more credible.

← This helps in predicting **forced** variability signals

Two Kinds of Climate Prediction Systems with CESM

“Uninitialized”

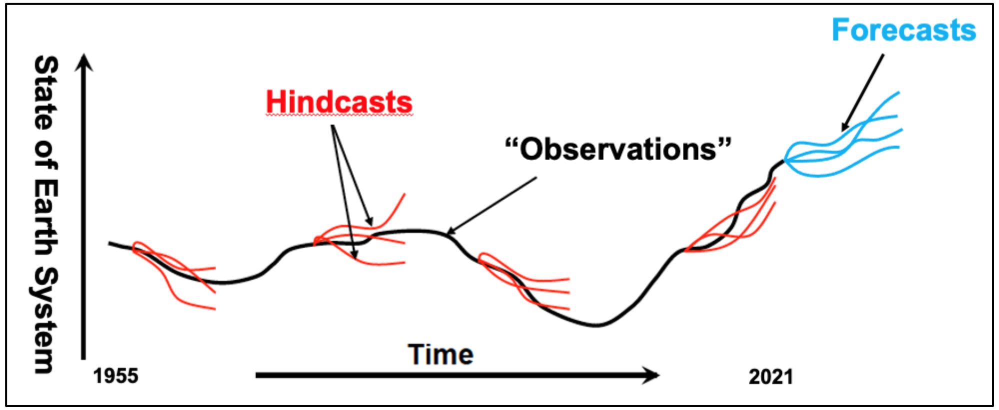
- Skill comes from accurately simulating **forced** variability & change
- Expect skill for long timescales, large spatial scales
- Examples: CESM1 LE (Kay et al., 2015, 10.1175/BAMS-D-13-00255.1)
  CESM2 LE (Rodgers et al., 2021, 10.5194/esd-12-1393-2021)



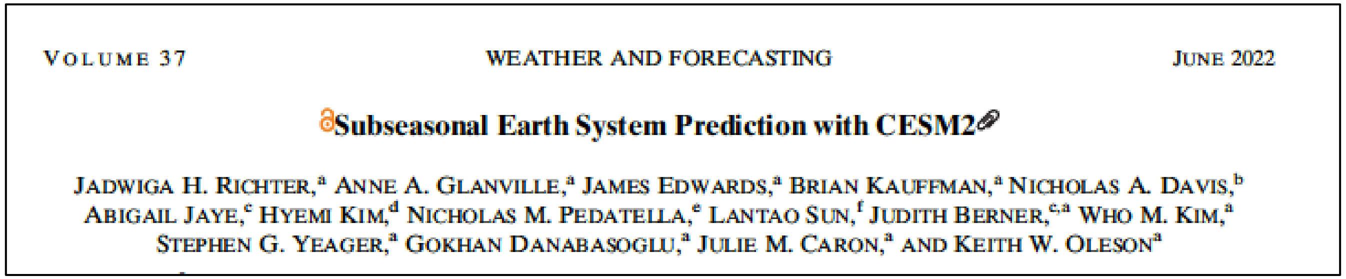
Kay et al (2015)

“Initialized”

- Skill comes from accurately simulating both **forced** & **internal** components
- Expect improved skill for short timescales, small spatial scales
- Examples:
  CESM2 S2S (Richter et al., 2021, 10.1175/WAF-D-21-0163.1)
  CESM2 SMYLE (Yeager et al., 2022, 10.5194/gmd-15-6451-2022)
  CESM1 DPLE (Yeager et al., 2018, 10.1175/BAMS-D-17-0098.1)



S2S Prediction with CESM


VOLUME 37 WEATHER AND FORECASTING JUNE 2022

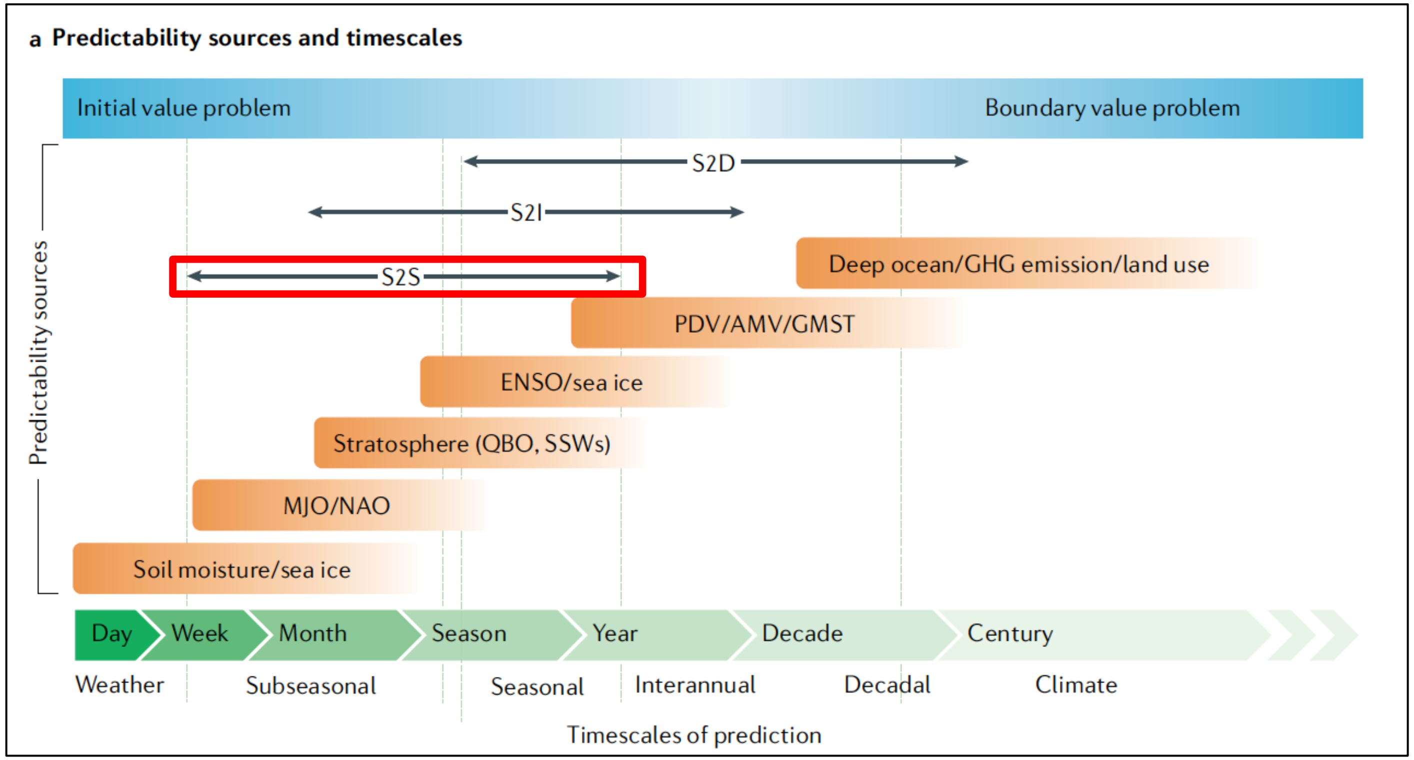
Subseasonal Earth System Prediction with CESM2

JADWIGA H. RICHTER,[a] ANNE A. GLANVILLE,[a] JAMES EDWARDS,[a] BRIAN KAUFFMAN,[a] NICHOLAS A. DAVIS,[b] ABIGAIL JAYE,[c] HYEMI KIM,[d] NICHOLAS M. PEDATELLA,[e] LANTAO SUN,[f] JUDITH BERNER,[c,a] WHO M. KIM,[a] STEPHEN G. YEAGER,[a] GOKHAN DANABASOGLU,[a] JULIE M. CARON,[a] AND KEITH W. OLESON[a]

S2S system design:

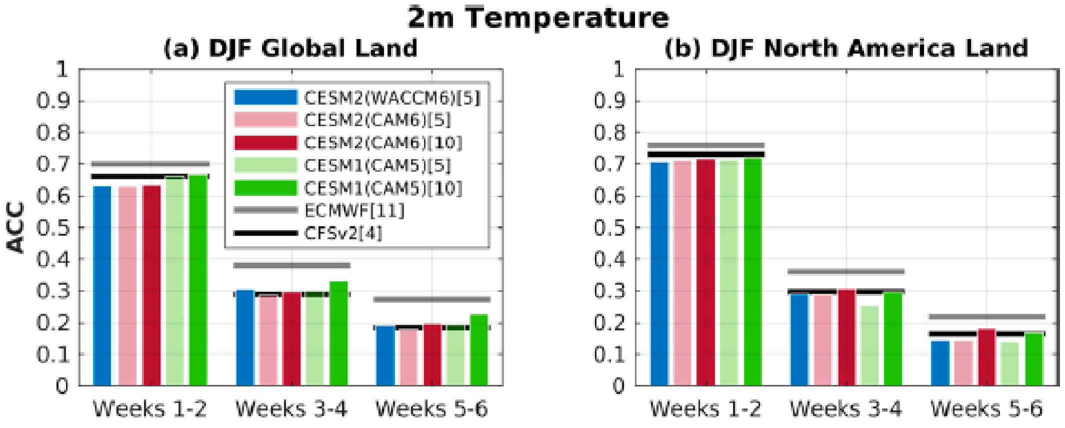
- Weekly initializations (1999-2020)
- 45-day simulations
- 10-member ensembles

➔ ~1,600 sim-years

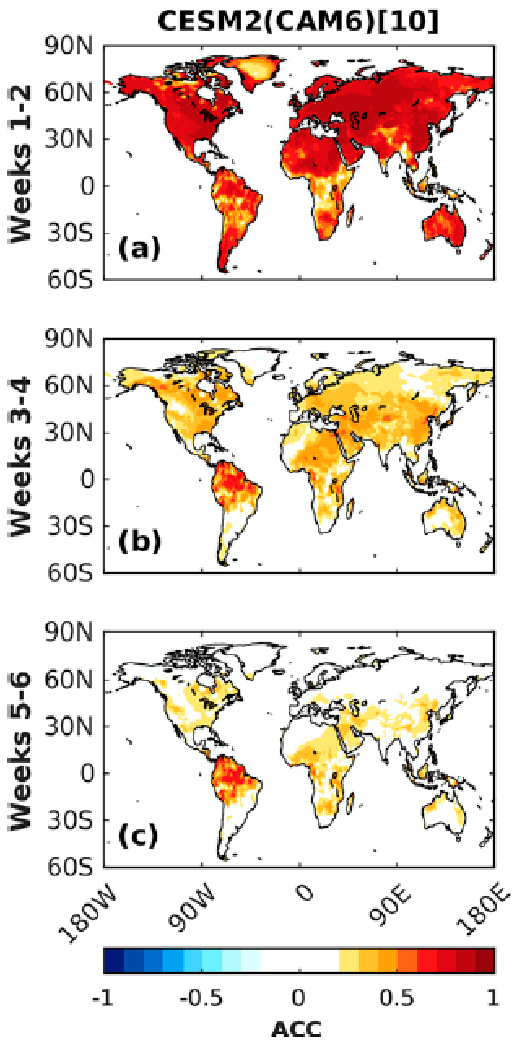


Meehl et al. (2021, *Nature Reviews*, https://doi.org/10.1038/s43017-021-00155- x)

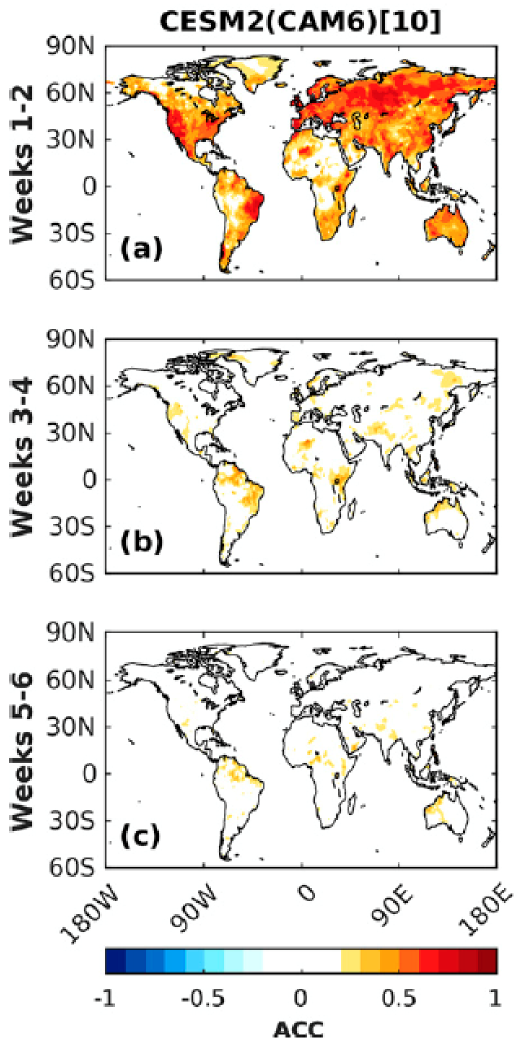
S2S Prediction with CESM



DJF 2m Temperature:



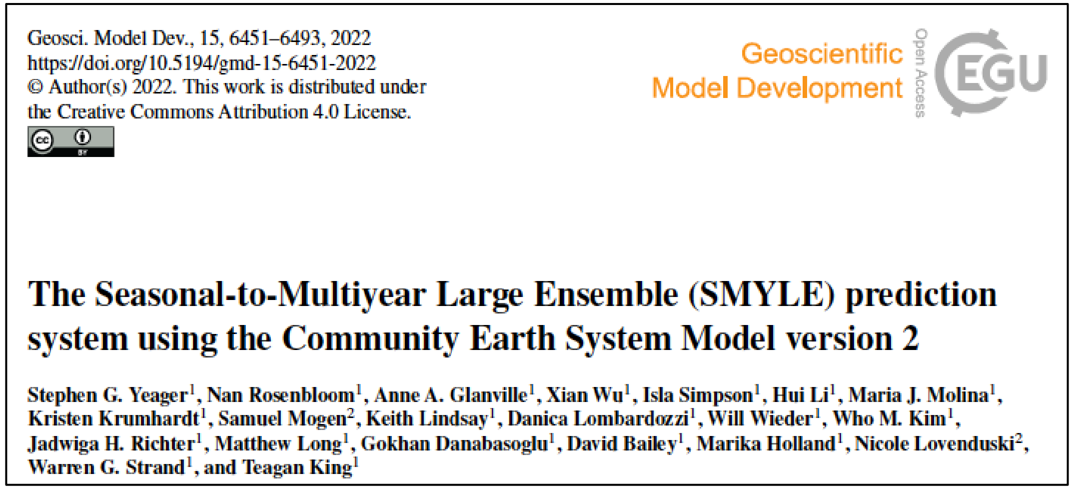
DJF Precipitation:



- Much lower skill for precipitation than temperature, consistent with previous findings
- CESM systems comparable to (or slightly better than) CFSv2; slightly lower than ECMWF

Richter et al. (2022)

S2I Prediction with CESM


Geosci. Model Dev., 15, 6451–6493, 2022
https://doi.org/10.5194/gmd-15-6451-2022

Geoscientific Model Development
Open Access
EGU

The Seasonal-to-Multiyear Large Ensemble (SMYLE) prediction system using the Community Earth System Model version 2

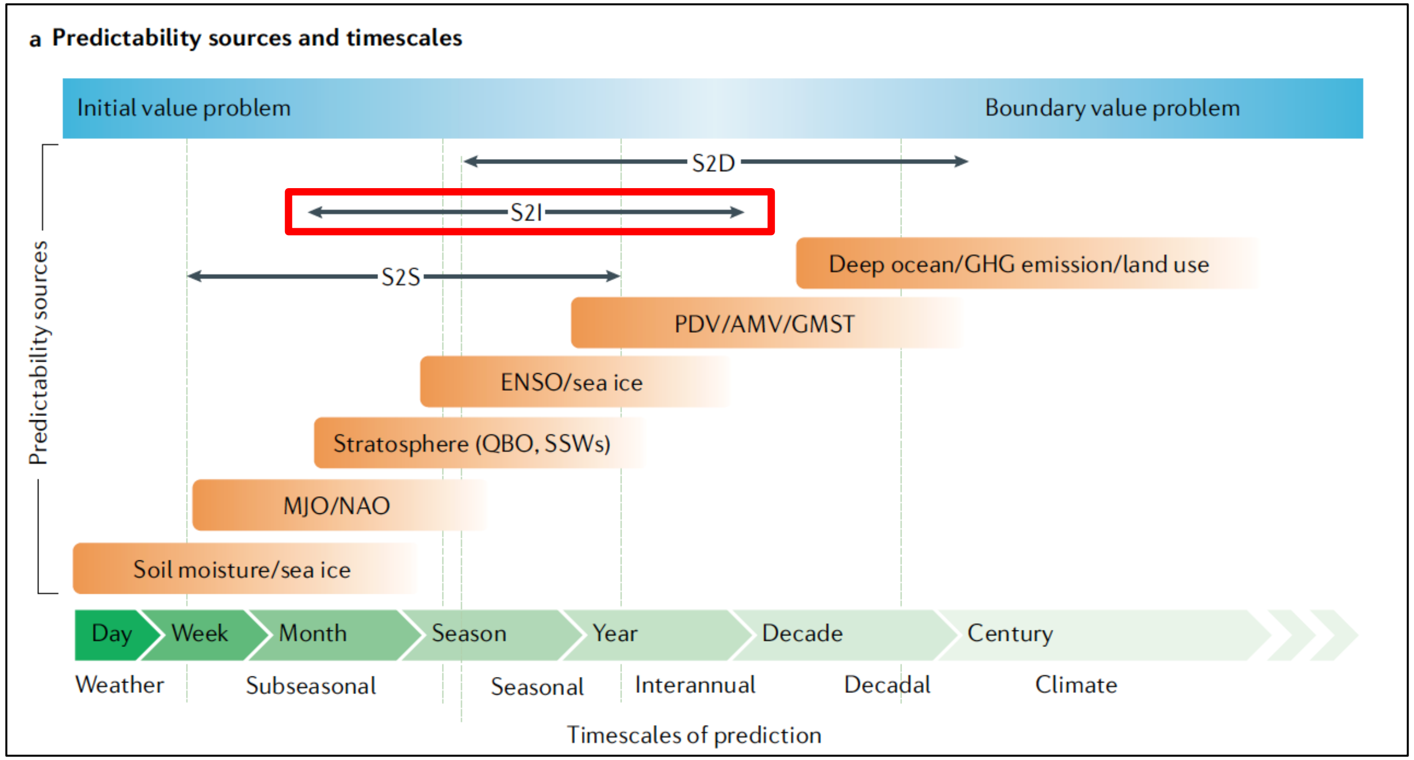
Stephen G. Yeager[1], Nan Rosenbloom[1], Anne A. Glanville[1], Xian Wu[1], Isla Simpson[1], Hui Li[1], Maria J. Molina[1], Kristen Krumhardt[1], Samuel Mogen[2], Keith Lindsay[1], Danica Lombardozzi[1], Will Wieder[1], Who M. Kim[1], Jadwiga H. Richter[1], Matthew Long[1], Gokhan Danabasoglu[1], David Bailey[1], Marika Holland[1], Nicole Lovenduski[2], Warren G. Strand[1], and Teagan King[1]

"CESM2-SMYLE"

S2I system design:

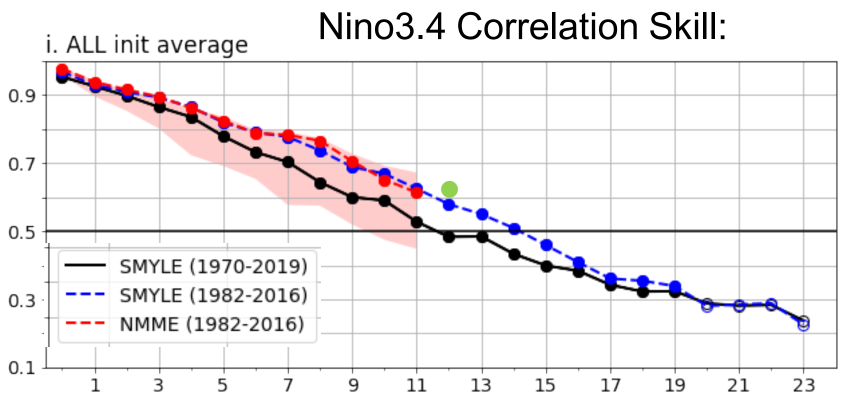
- Quarterly initializations (1st of Nov/Feb/May/Aug 1958-2020)
- 24-month simulations
- 20-member ensembles

➔ ~10,000 sim-years

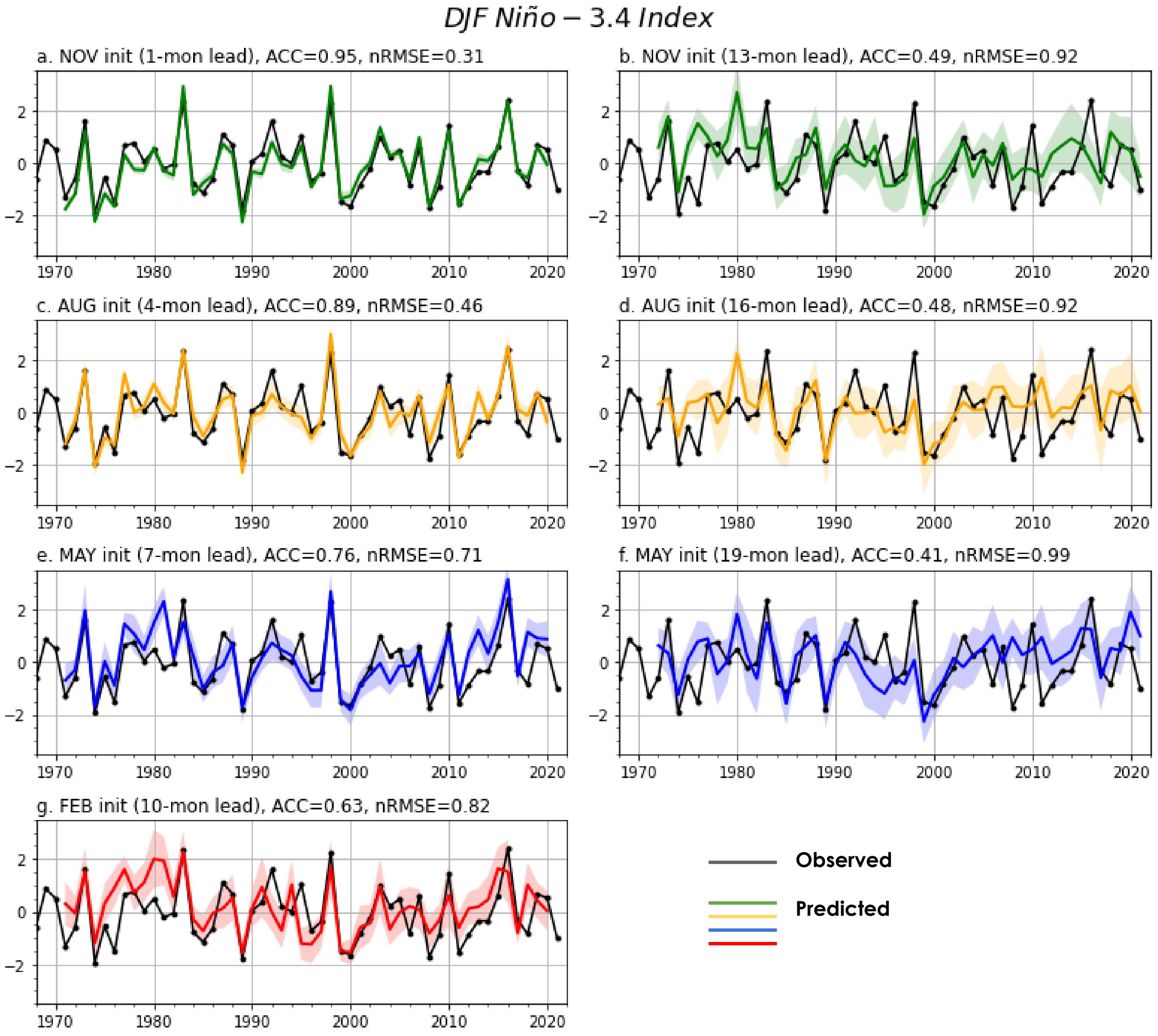


Meehl et al. (2021, *Nature Reviews*, https://doi.org/10.1038/s43017-021-00155- x)

S2I Prediction with CESM



- CESM2-SMYLE is competitive with other leading ENSO prediction systems (NMME, ECMWF)



Yeager et al. (2022)

S2D Prediction with CESM

PREDICTING NEAR-TERM CHANGES IN THE EARTH SYSTEM

A Large Ensemble of Initialized Decadal Prediction Simulations Using the Community Earth System Model

S. G. Yeager, G. Danabasoglu, N. A. Rosenbloom, W. Strand, S. C. Bates, G. A. Meehl, A. R. Karspeck, K. Lindsay, M. C. Long, H. Teng, and N. S. Lovenduski

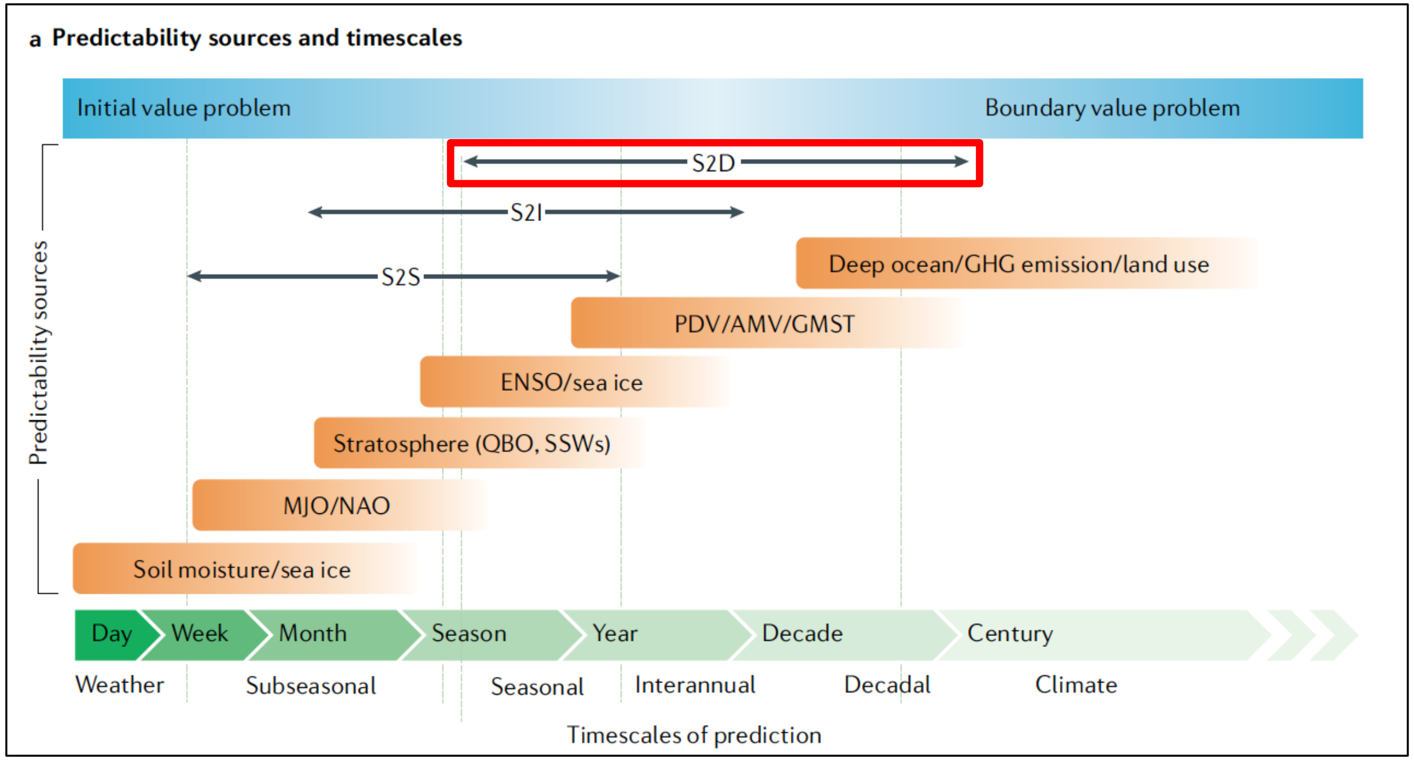
BAMS 2018

“CESM1-DPLE”

S2D system design:

- Annual initializations (Nov. 1st 1954-2020)
- 122-month simulations
- 40-member ensembles

➔ ~27,000 sim-years



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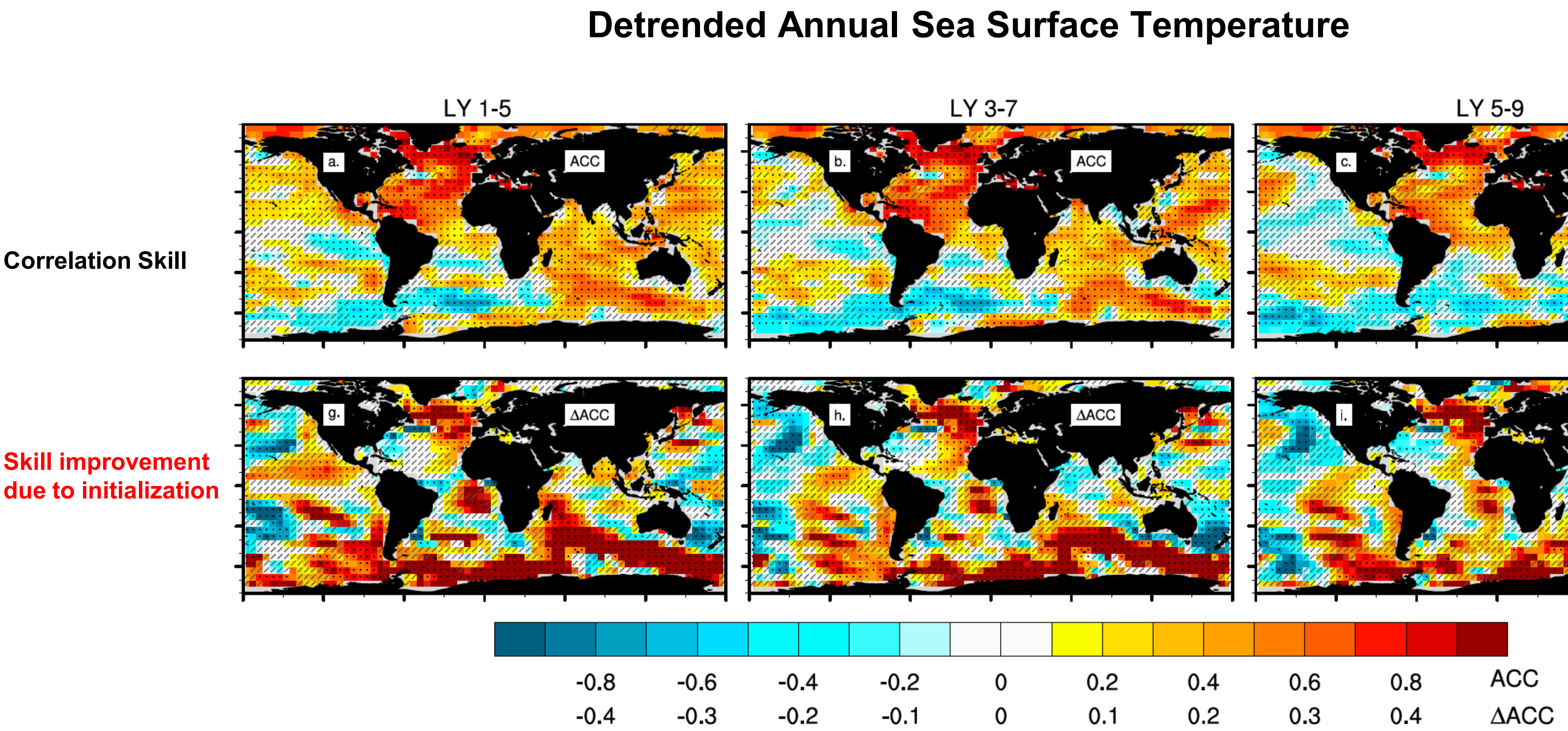
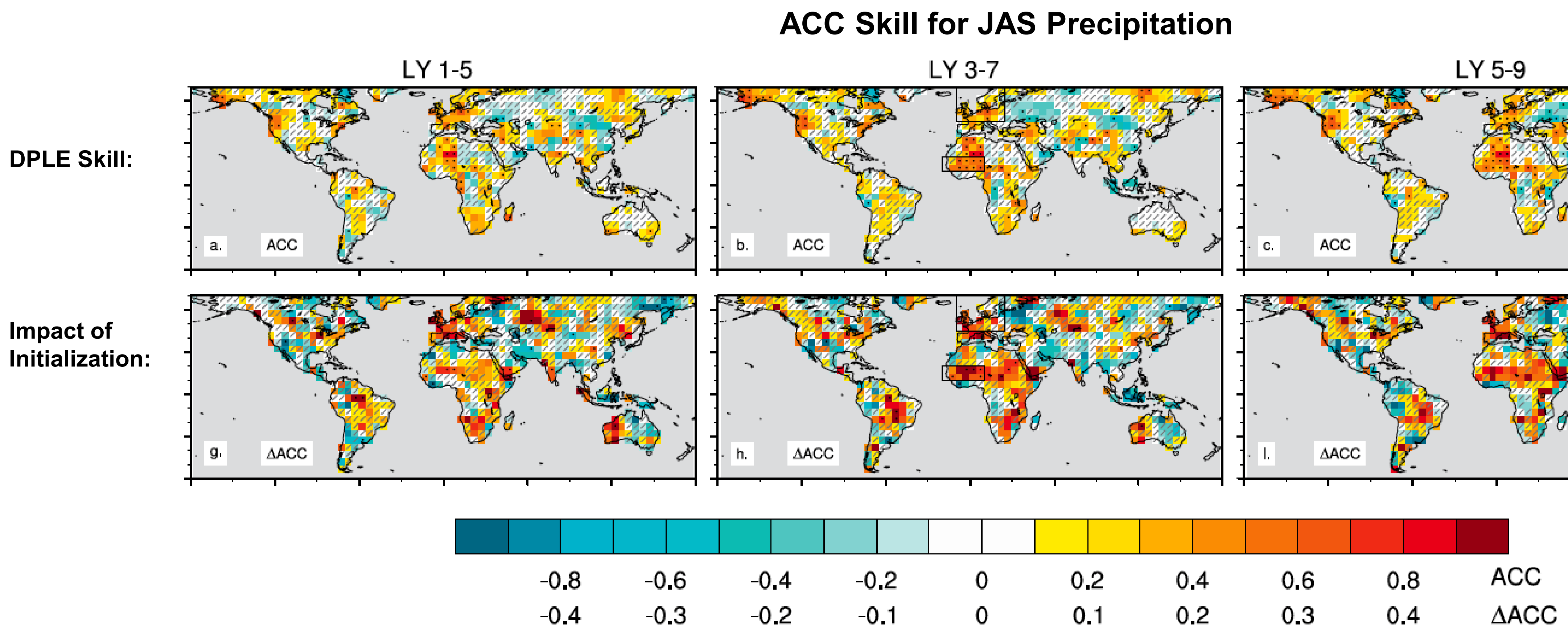
S2D Prediction with CESM



Detrended skill reveals more AMV-like improvement with initialization. Some improvement for PDV, but eastern Pacific skill remains low.

Yeager et al. (2018, 10.1175/BAMS-D-17-0098.1)

S2D Prediction with CESM

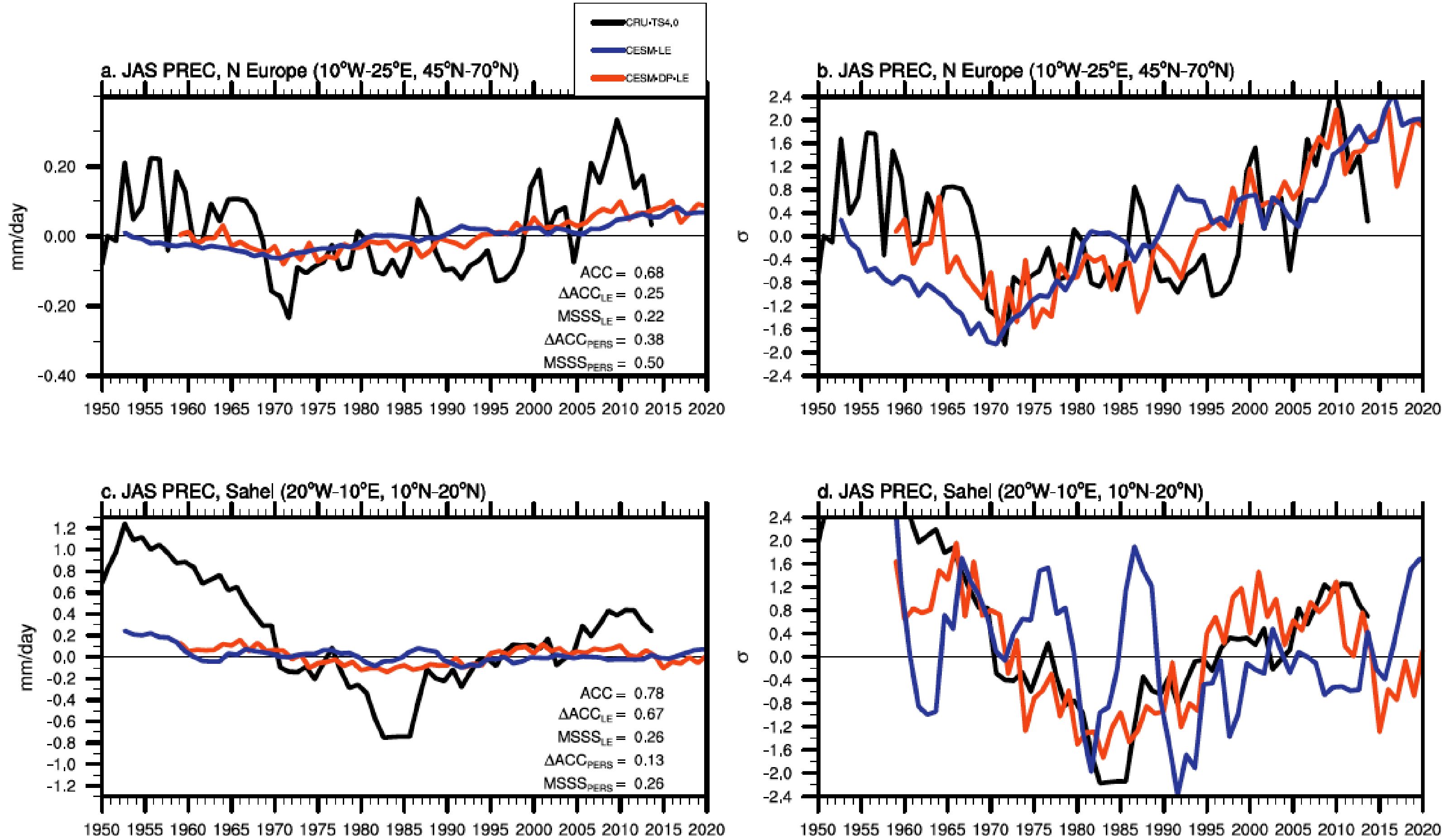


- Evidence of decadal “initialization shock”
- High skill (and clear benefit of initialization) in select regions (Sahel, N. Europe)

Yeager et al. (2018)

S2D Prediction with CESM

- DPLE FY3-7
- Skillful predictions of precip, but amplitude is weak (signal-to-noise paradox)



Yeager et al. (2018)

Outstanding Questions

- **How/where can we increase climate prediction skill?**
  - initialization
  - post-processing (AI/ML)
  - general model fidelity (e.g., model resolution, model physics)
  - more signal, less noise (Scaife & Smith, 2018, doi:10.1038/s41612-018-0038-4; Smith et al., 2020, 10.1038/s41586-020-2525-0)

- **What are the coupled mechanisms at work in initialized ensemble prediction simulations? What explains skillful (or unskillful) S2S2D predictions?**

- **What can we learn about predictability & mechanisms from multi-model systems?**

- **How can we enhance connections with potential end-users?**

Interested? Get Involved!

- Analyze ESPWG datasets
- Propose new experiments that can utilize ESPWG compute allocation
- Share your work at future meetings

Contacts:

- ESPWG Co-chairs: Steve Yeager (yeager@ucar.edu), Kathy Pegion (kpegion@ou.edu)
- ESPWG Liaison: Sasha Glanville (sglanvil@ucar.edu)
- https:// www.cesm.ucar.edu /working-groups/earth-system/

Extra Slides

Model Drift & Drift Correction

- Biased models initialized from realistic states “drift” back towards model attractor

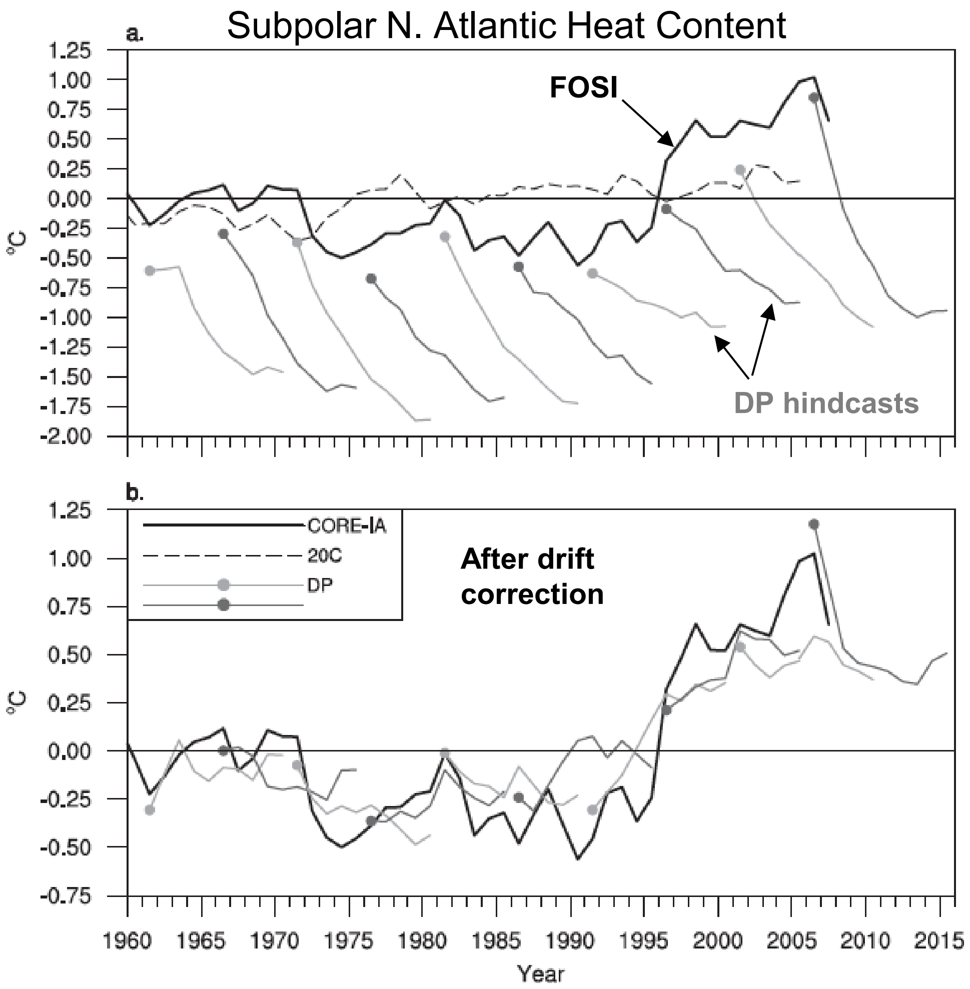
- Standard post-processing to remove hindcast drift:

$$f'_{i\tau} = f_{i\tau} - \overline{f_\tau} = f_{i\tau} - \frac{1}{N}\sum_{1}^{N} f_{i\tau}$$

for hindcast samples $i = 1 \ldots N$ and forecast lead time τ

- Other more sophisticated methods have been explored:

Kharin et al. (2012, *GRL*, https://doi.org/10.1029/2012GL052647)
Meehl et al. (2022, *CLI DYN*, https://doi.org/10.1007/s00382-022-06272-7)



Yeager et al. (2012, https://doi.org/10.1175/JCLI-D-11-00595.1)

Predicting AMV Impacts: Sea Ice


Geophysical Research Letters

RESEARCH LETTER
10.1002/2015GL065364

Predicted slowdown in the rate of Atlantic sea ice loss

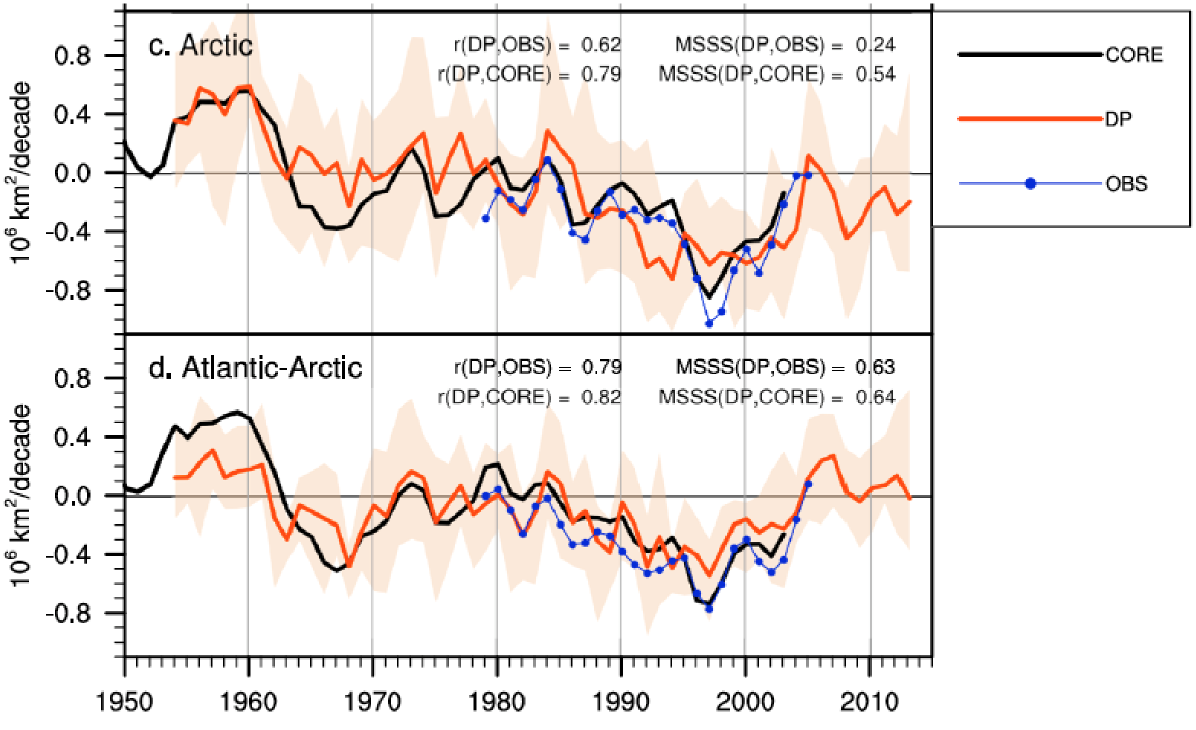
Stephen G. Yeager[1], Alicia R. Karspeck[1], and Gokhan Danabasoglu[1]

[1]Climate and Global Dynamics Laboratory, National Center for Atmospheric Research, Boulder, Colorado, USA

Key Points:
- Ocean thermohaline circulation

- 10-member CESM1-DP
- Predictable decadal changes in N. Atlantic ocean thermohaline circulation (THC) strength & northward heat transport (related to low-frequency NAO buoyancy forcing) translates into predictable changes in the rate of Arctic winter sea ice decline.
- Rapid sea ice decline in 1990s was associated with THC spinup, & ongoing and future THC spindown (weak NAO forcing after 1997) will result in a slowdown in the rate of Arctic winter sea ice loss.

10-year JFM Sea Ice Extent Trends



Yeager et al. (2015, 10.1002/2015GL065364)

Start year of 10-year trend

Predicting AMV Impacts: Sea Ice

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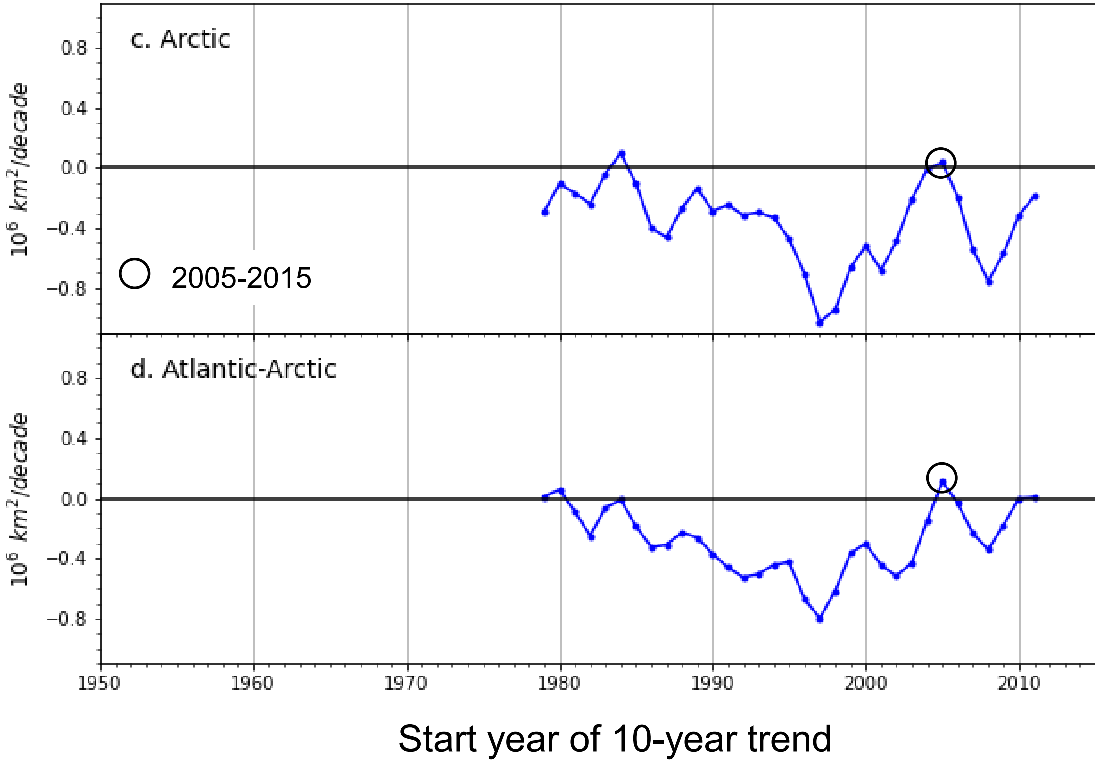
How accurate was the forecast?

10-year Observed Trends extended through 2011-2021



10-year JFM Sea Ice Extent Trends